A Force-Driven Evolutionary Approach for Multi-objective 3D Differentiated Sensor Network Deployment

Liang-Che Wei, Chih-Wei Kang and Jian-Hung Chen*
Department of Computer Science and Information Engineering
Chung-Hua University, Hsin-Chu 300, Taiwan
*jh.chen@ieee.org**

ABSTRACT

This paper describes a novel force-driven evolutionary approach for solving multi-objective 3D deployment problems in differentiated wireless sensor networks (WSNs). WSN is a wireless network consisting of spatially distributed autonomous sensors to monitor physical or environmental conditions. Deciding the location of sensor to be deployed on a terrain with the consideration of different criteria is an important issue for the design of wireless sensor network. A multi-objective genetic algorithm with a force-driven method is proposed to solve 3D differentiated WSN deployment problems with the objectives of the coverage of sensors, satisfaction of detection levels, and energy conservation. The preliminary experimental results demonstrated that the proposed approach is capable of obtaining a set of non-dominated solutions for multi-objective 3D differentiated WSN deployment problems.

1. INTRODUCTION

A wireless sensor network (WSN) is a wireless network consisting of spatially distributed autonomous sensors to monitor physical or environmental conditions. Sensor nodes of a WSN are deployed over a region to sense events on geographical areas and transmit collected data to a sink node for further operations. Depending on the requirements, sensors could be deployed in diverse scenarios [4,9]. Therefore, deciding the location of sensor to be deployed on a terrain is an important issue. Several different objectives should be considered and fulfilled in the design phase of WSNs, such as the coverage and accuracy, reaction time and survivability of the sensor network. However, these objectives may be in conflict with one another and of different importance to mission planners [10].

Coverage is one of the fundamental issue in the deployment of WSNs. WSNs have to maintain sufficient coverage quality in order to capture the timely changing targets [13]. For enhanced coverage, a large number of sensors are typically deployed in the sensor field and, if the coverage areas of multiple sensors overlap, they may all report a target in their respective zones [3].

Differentiated sensor network deployment, which considers the satisfaction of detection levels in different geographical characteristics, is also an important issue [1]. In some specially designated WSN applications, such as underwater sensor deployment, mudflows and landslide monitoring, depending on the event's location, the supervised area may require different detection levels. Therefore, the sensing requirements of these applications are not uniformly distributed within the area. As a result, the deployment strategy of WSN should take into consideration the geographical characteristics of the monitored events.

Energy conservation for the lifetime of sensors is another rising issue [5]. Due to the limited energy resource in each sensor node, utilizing sensors in an efficient manner so as to increase the lifetime of the network is an important task in the design phase of WSNs. There are two different approaches: scheduling and adjusting methods, to the problem of conserving energy in sensor networks. We focus on adjusting the sensing range of each sensor in order to reduce the overlaps among sensing ranges while keep the detection ability above a predefined detection level.

In this paper, a 3D differentiated WSN deployment problem is formulated into a multi-objective optimization problem. Three objectives are to be optimized: maximizing coverage of sensors, satisfying

978-1-4244-5113-5/09/$25.00 (c)2009 IEEE

the required probability of detection level, and minimizing the detection power by adjustable sensing range. A multi-objective genetic algorithm (MOGA) framework with a novel force-driven method is proposed to solve these problems.

2. RELATED WORK

2.1. WSN Deployment Problem

Coverage issue is one of the most important tasks in WSN. The ultimate goal is to have each location in the physical space of interest within the sensing range of at least one sensor. However, due to the number of sensors is limited, complete coverage cannot be guaranteed. Therefore, many approaches are proposed to deal with the 2D coverage problem [7, 10]. Recently, Oktug et al. [9] proposed an approach to solve coverage problem by simulating sensor deployment strategies on a 3D terrain model and to find answers to questions that how many sensors are needed to cover a specified 3D terrain at a specified coverage percentage.

Different applications require different degrees of sensing coverage. While some applications may require a complete coverage in a region, others may only need a high percentage of coverage. Such WSN is called differentiated WSN [1]. Take underwater sensor deployment [2] as an example, sensor field of underwater is characterized by the geographical irregularity of the sensed events because some area may be inaccessible or the event area may not be uniformly distributed. To efficiently monitor such area with differentiated detection levels, fulfillment of detection levels in different area is the major concerns instead of maximizing the coverage of sensors [11]. Aitsaadi et al. [1] proposed a probabilistic event detection model. In this model, each grid point has a required minimum probability detection threshold. A tabu search method is proposed to solve this differentiated WSN deployment problem.

In recent years, utilizing limited energy efficiently in a wireless sensor network has become an important issue. Several techniques, such as scheduling models and sleep models [4, 8, 12], have been proposed to extend the lifetime of WSNs.

2.2. Multi-objective Evolutionary Optimization

Assume the multi-objective functions are to be minimized. Mathematically, multi-objective optimization problems (MOOPs) can be represented as the following vector mathematical programming problems

$$\mathit{Minimize} \quad F(Y) = \{F_1(Y), F_2(Y), ..., F_i(Y)\}, \tag{1}$$

where Y denotes a solution and $F_i(Y)$ is generally a nonlinear objective function. Pareto dominance relationship and some related terminologies are introduced below. When the following inequalities hold between two solutions Y_1 and Y_2, Y_2 is a non-dominated solution and is said to dominate Y_1 ($Y_2 \succ Y_1$):

$$\forall i : F_i(Y_1) \geq F_i(Y_2) \wedge \exists j : F_j(Y_1) > F_j(Y_2). \tag{2}$$

When the following inequality hold between two solutions Y_1 and Y_2, Y_2 is said to weakly dominate Y_1 ($Y_2 \succeq Y_1$):

$$\forall i : F_i(Y_1) \geq F_i(Y_2). \tag{3}$$

A feasible solution Y^* is said to be a Pareto-optimal solution if and only if there does not exist a feasible solution Y where Y dominates Y^*.

By making use of Pareto dominance relationship, multi-objective evolutionary algorithms (MOEAs) [6] are capable of performing the fitness assignment of multiple objectives without using relative preferences of multiple objectives.

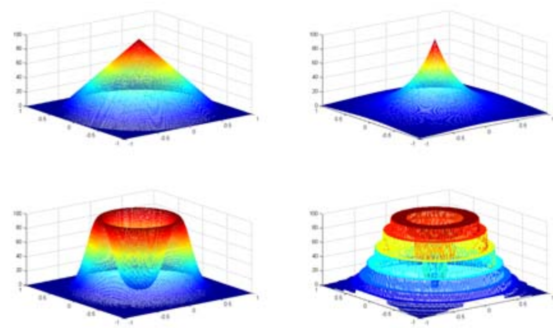

Figure 1. Terrain with different required detection levels: decreasing linear, normal, Poisson, and exponential distributions.

3. PROBLEM STATEMENT

3.1. Notations

In order to formulate problems, the following notations are introduced:

- i : sensor index, $i = 1,2,3,\ldots,N$.
- j : grid point index, $j = 1,2,3,\ldots,M$.
- k : sensing range index, $k = 1,2,3,\ldots,K$.

3.2. Environment

We assume that N sensors $s_1, s_2, \ldots, s_N$ are deployed to cover the sensor field. Let the sensor field T consist of n_x, n_y, and n_z grid points $p_1, p_2, \ldots, p_M$ in the x, y, and z dimensions, respectively [3]. Each sensor has an initial sensor energy E and has the capability to adjust its sensor range. Sensing range options are $r_1, r_2, \ldots, r_K$, corresponding to energy consumptions of $e_1, e_2, \ldots, e_K$ and detection error ranges $f_1, f_2, \ldots, f_K$ ($f_k < r_k$) [4]. We assume that each grid point p_j in sensor field is associated a required minimum probability detection level, denoted $t(p_j)$.

3.3. Mathematical Formation of 3D Deployment Problem

3.3.1. Maximization of Coverage.

In many WSN applications, the main task is the surveillance of certain geographical areas [9]. Target location can be simplified considerably if the sensors are placed in such a way that every grid point in the sensor field is covered by sensors [3]. Assume that sensor s_i is deployed at grid point. For any grid point p_j, the Euclidean distance between sensor s_i and grid point p_j is denoted as

$$d(s_i, p_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{4}$$

, where x_i, x_j, y_i, y_j, z_i and z_j are coordinate location values. The following equation shows a binary coverage model expressing the coverage $c_b(s_i, p_j)$ of a grid point p_j by sensor s_i.

$$c_b(s_i, p_j) = \begin{cases} 1, & if\ d(s_i, p_j) < r_k(s_i) \\ 0, & otherwise \end{cases} \tag{5}$$

, where $r_k(s_i)$ is the sensing range of the sensor s_i.

The coverage rate optimization problem F_1 can be defined by

$$Max. \quad F_1 = \frac{\sum_{j=1}^{M} c_b(p_j)}{M} \tag{6}$$

, where $c_b(p_j)$ is the coverage of all sensors at grid point p_j by the Equation (5). This objective is to be maximized.

3.3.2. Maximization of Differentiated Detection Levels.

Considering differentiated detection levels, assumed that each grid point p_j in sensor field T is associated a required minimum detection level $t(p_j)$. A terrain may have different required detection levels, as illustrated in Figure 1. A good deployment for differentiated WSN should satisfy the following condition: for each p_j in T, the measured detection probability of p_j should be greater than or equal to $t(p_j)$ [1].

A probabilistic detection model for sensor deployment [1] is adopted into our model. Assume that event detection probability of a sensor diminishes as its distance to the sensed point increases. A probabilistic detection model of sensors is expressed as

$$c_p(s_i, p_j) = \begin{cases} 0, & \text{if } r_k(s_i) + f_k(s_i) \le d\left(s_i, p_j\right) \\ e^{-\lambda\alpha^{\beta}}, & \text{if } r_k(s_i) - f_k(s_i) < d\left(s_i, p_j\right) < \\ & \quad r_k(s_i) + f_k(s_i) \\ 1, & \text{if } r_k(s_i) - f_k(s_i) \ge d\left(s_i, p_j\right) \end{cases} \tag{7}$$

, where $\alpha = d(s_i, p_j) - (r_k(s_i) - f_k(s_i))$, λ and β are parameters that measure the detection probabilities when an object is within a certain distance from the sensor, and $f_k(s_i)$ is the error ranges of the sensor s_i. Each sensor s_i has a detection probability $c_p(s_i, p_j)$ at grid point p_j. A grid point p_j might be covered by more than one detection range of different sensors [8]. When a detection area is overlapped by multiple sensors, the closer are the sensors to each other, the higher is the detection probability of the grid points [7]. The conjunctive detection probability of all sensors at grid point p_j is given by

$$c_p(p_j) = 1 - \prod_{i=1}^{N} (1 - c_p(s_i, p_j)). \tag{8}$$

The optimization of the satisfaction required probability of detection level F_2 is expressed by:

$$Max. \quad F_2 = \frac{\sum_{j=1}^{M} DP(p_j)}{\sum_{j=1}^{M} t(p_j)} \tag{9}$$

,where $DP(p_j) = \begin{cases} t(p_j) & if\ c_p(p_j) - t(p_j) \ge 0 \\ 0 & otherwise \end{cases}$.

This objective is to be maximized.

3.3.3. Minimization of Energy Consumption

In terms of energy consumption, we only consider the energy used in sensing, but not including the power consumed by radio communication and computation. The sensing ranges of a sensor determine the energy consumed by the sensor [4]. We adopted an energy model in our evaluation. The power consumption is proportional to the square of the sensing range r_k [11]. The energy consumption model is expressed as follows:

$$e_k(s_i) = \mu \times r_k(s_i)^2, \tag{10}$$

where μ is an energy consumption parameter. The optimization of the detection power minimization with adjustable sensing range F_3 can be formulated as

$$Min. \quad F_3 = \frac{\sum_{i=1}^{N} e_k(s_i)}{\sum_{i=1}^{N} e_{\max}(s_i)} \tag{11}$$

, where $e_{max}(s_i)$ is the maximum detection range of each sensor. This objective is to be minimized.

4. FORCE-DRIVEN MULTI-OBJECTIVE GENETIC ALGORITHM (FD-MOGA)

4.1. Chromosome Representation

A chromosome has gene information for solving the problem in FD-MOGA. Each chromosome has fixed gene size, which is determined by the number of sensors in the WSN. Each gene has a *x, y,* and *z* coordinate location and a sensing range. The ranges of each gene of coordinate location are [0, n_x], [0, n_y], and [0, n_z] in the *x, y,* and *z* dimensions. Hence these sensors will have coordinate values to denote their location. Each gene of sensing range is one of $r_1, r_2, \ldots, r_K$, which represent the detection ability of the sensor.

4.2. Fitness Assignment

We use a generalized Pareto-based scale-independent fitness function (GPSIFF) considering the quantitative fitness values in Pareto space for both dominated and non-dominated individuals. Let the fitness value of an individual *Y* be a tournament-like score obtained from all participant individuals by the following function:

$$F(Y) = p - q + c \tag{12}$$

, where *p* is the number of individuals which can be dominated by the individual *Y*, and *q* is the number of individuals which can dominate the individual *Y* in the objective space. *c* is set to the number of all participant individuals.

4.3. Genetic Operators

The genetic operators used in the proposed approach are widely used in literature. The selection operator uses a binary tournament selection without replacement. The uniform crossover is used in FD-MOGA. A simple mutation operator is used to alter genes. For each gene, randomly generate a real value from the range [0, 1]. If the value is smaller than the mutation probability p_m, replace its index with a randomly generated integer among its possible values.

4.4. Repulsion and Attraction Force Mutation

To prevent sensors from overly centering in some positions in individuals, a force-driven method is introduced. The proposed force-driven method consists of two forces: repulsion force and attraction force. While the density of sensors within a certain space is high, a repulsion force mutation is to increase the degree of spread between sensors. On the contrary, while the density of sensors is low, an attraction force mutation is used to centralize sensors within a certain space. The procedure of repulsion and attraction force mutation is written as follows:

Step 1: Space Division Divide the sensor field *T* into bn_x, bn_y, and bn_z large grid space $bp_1, bp_2, \ldots, bp_L$, where $n_x > bn_x$, $n_y > bn_y$, and $n_z > bn_z$.

Step 2: Position Compute the position of sensors within each large grid space bp_l, $l = 1,2,\ldots, L$. Partition the sensors within the large grid space bp_l into a set S_l.

Step 3: Statistics Calculate the number of sensors, b_l, in each set S_l .

Step 4: Repulsion Mutation If the number b_l of sensors in a large grid space bp_l is bigger than one, repulse the positions of sensors in S_l from their centroid with one grid point in every dimension, and increase one level of sensing range in these sensor.

Step 5: Attraction Mutation If the number b_l of sensors in large grid space bp_l is equal to one, let the sensors adjacent to the large grid space bp_l be attracted and move to the position of the sensor in S_l with one grid point for every dimension, and decrease one level of sensing range in these sensors.

4.5. Procedure of FD-MOGA

An elitism strategy is adopted. An elite set *E* with capacity E_{max} will maintain all the best non-dominated solutions generated so far. The procedure of FD-MOGA is written as follows:

Input: population size N_{pop}, recombination probability p_c, mutation probability p_m, the number of maximum generations G_{max}.

Output: The optimum solutions ever found in *P*.

Step 1: Initialization Randomly generate an initial population *P* of N_{pop} individuals, and create an empty elite sets *E*.

Step 2: Evaluation For each individual in the population, compute all objective function values F_1, F_2, and F_3.

Step 3: Fitness assignment Assign each individual a fitness value by using GPSIFF.

Step 4: Update elitist Add the non-dominated individuals in *E*. Considering all individuals in *E*, remove the dominated ones in *E*. If the number of non-dominated individuals in *E* is larger than E_{max}, randomly discard excess individuals.

Step 5: Selection Select N_{pop} - N_{ps} individuals from the population to form a new population using the binary tournament selection and random select N_{ps} individuals from E to form a new population, where $N_{ps} = N_{pop} \times p_s$ and p_s is a selection proportion. If N_{ps} is greater than the number N_E of individuals in E, let $N_{ps} = N_E$..

Step 6: Recombination Perform the uniform crossover operation with a recombination probability p_c.

Step 7: Mutation Apply the simply mutation operator to each gene in the individuals with a mutation probability p_m.

Step 8: Repulsion and Attraction Mutation Execute the repulsion and attraction mutation to each individual with two probabilities p_r and p_a.

Step 9: Termination test If a stopping condition is satisfied, stop the algorithm. Otherwise, go to Step 2.

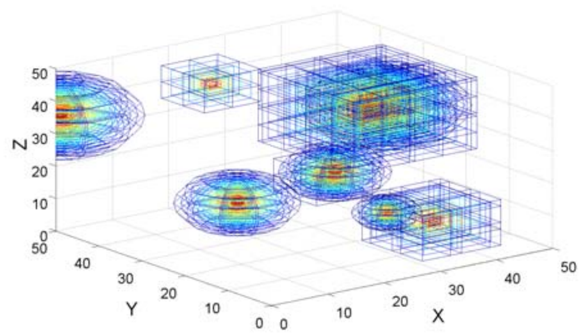

Figure 2. A terrain with decreasing linear detection levels.

5. RESULT AND DISCUSSION

5.1. Simulation Environment and Parameters

A 3D WSN deployment benchmark generator for WSN environment is designed to generate different scale of sensor fields with different models of detection probability levels. A sensor field with 50×50×50 grid points is generated. The same terrain with four different required minimum detection probability levels: decreasing linear, normal, Poisson, and exponential distributions, are illustrated as four different benchmarks. Figure 2 illustrates a terrain with linear decreasing levels. For the sensors of WSN, we assume each sensor has five adjustable sensing ranges 6, 8, 10, 12, 14, and the detection error ranges are half of the sensing range of each sensor. The power consumption parameter μ is 1. The probabilistic detection model parameter β is 0.5 and the detection radio wave parameter λ is 0.5.

The parameter settings of the proposed algorithm are listed as follows: population size N_{pop}=200, maximum number elite set of individuals E_{max}=10000, selection elite set proportion p_s=0.2, division of large grid space 5×5×5, recombination probability p_c=0.9, mutation probability p_m=0.01, repulsion probability p_r=0.1, attraction probability p_a=0.1, the number of maximum generations G_{max}=500 and 1000. Thirty independent runs are conducted for each problem. The number of sensor nodes to be deployed is limited to 20.

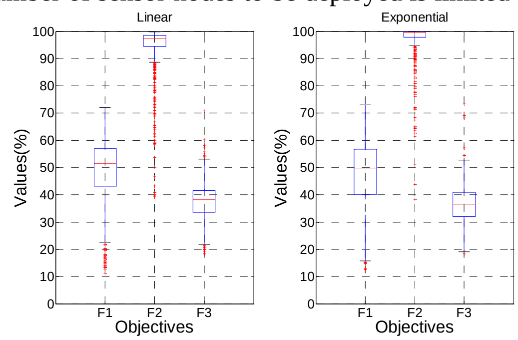

Figure 3. Box plots of non-dominated solutions for solving the 3D deployment problem with linear and exponential detection levels, using 20 sensors.

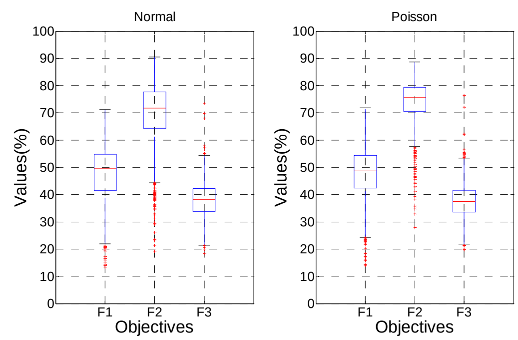

Figure 4. Box plots of non-dominated solutions for solving the 3D deployment problem with normal and Poisson detection levels, using 20 sensors.

Figures 3-4 depict the box plots of obtained non-dominated solutions. The results indicate that different detection levels pose different difficulties for FD-MOGA. The problems with normal and Poisson detection levels are more difficult to find a good deployment plan than problems with decreasing linear and exponential detection levels using the same number of sensors. The number of sensors required for a terrain with normal and Poisson detection levels should be bigger than the same terrain with decreasing linear and exponential detection levels.

A naïve MOGA without elitism and repulsion and attraction mutation is also implemented. The coverage metric *C(A,B)* of two solution sets A and B [6] used to compare the performance of two corresponding algorithms, FD-MOGA and MOGA, considering all the objectives.

$$C(A,B) = \frac{\{a \in A, b \in B, a \succeq b\}}{|B|}. \tag{13}$$

The value $C(A, B)$=1 means that all individuals in B are weakly dominated by A. Figure 5 depict box plots of coverage metric of FD-MOGA and MOGA in solving the 3D deployment problems with four detection levels, using 20 sensors. The result demonstrates the effectiveness of the elitism and force-driven mutation used in FD-MOGA.

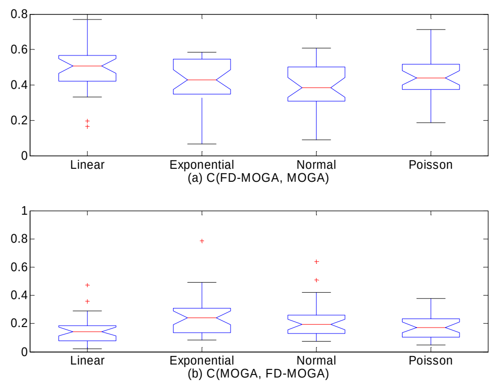

Figure 5. Box plots of coverage metric of FD-MOGA and MOGA for solving the 3D deployment problems with four detection levels, using 20 sensors.

6. CONCLUSION

In this paper, a force-driven multi-objective evolutionary approach is proposed to solve 3D differentiated WSN deployment problems. Experimental results demonstrated FD-MOGA is capable of optimizing coverage, satisfaction of detection levels, and energy conservation. Moreover, FD-MOGA can provide mission planers a set of non-dominated solutions for deployment of sensor nodes. The results also indicate that some problems with unusual detection levels requirements may require more sensor nodes for FD-MOGA than those of problems with usual detection levels requirements. Our future work will develop specialized techniques for 3D WSN deployment problems with unusual detection levels.

7. ACKNOWLEDGMENTS

This work was supported by the National Science Council of Taiwan, R.O.C. under Contract NSC-96-2221-E-216-037-MY2, and Chung-Hua University under Contract CHU-96-2221-E-216-037-MY2.

8. REFERENCES

[1] N. Aitsaadi, N. Achirt, K. Boussetta, and G. Pujolle, “A Tabu Search Approach for Differentiated Sensor Network Deployment,” in *Proc. of 5th IEEE Consumer Communications and Networking Conference, 2008. CCNC 2008*, pp. 163-167, 2008.

[2] N. Aitsaadi, N. Achir, K. Boussetta, and G. Pujolle, "Differentiated Underwater Sensor Network Deployment," in *Proc. of OCEANS 2007 – Europe*, pp.1-6, June 2007.

[3] K. Chakrabarty, S. S. Iyengar, H. Qi, and E. Cho, “Grid coverage for surveillance and target location in distributed sensor networks,” *IEEE Transactions on Computers*, vol. 51, no. 12, pp. 1448-1453, 2002.

[4] M. Cardei, J. Wu, and M. Lu, “Improving network lifetime using sensors with adjustable sensing ranges,” *International Journal of Sensor Networks*, vol. 1, no. 1/2, pp. 41-49, 2006.

[5] A. Dhawan, C. T. Vu, A. Zelikovsky, Y. Li, and S. K. Prasad, “Maximum Lifetime of Sensor Networks with Adjustable Sensing Range,” in *Proc. of Seventh ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing, 2006. SNPD 2006*, pp. 285-289, 2006.

[6] K. Deb. *Multi-Objective Optimization using Evolutionary Algorithms*. John Wiley & Sons, Chichester, UK, 2001.

[7] J. Jia, J. Chen, G.-R. Chang, and Y.-Y. Wen, “Efficient Cover Set Selection in Wireless Sensor Networks,” *Acta Automatica Sinica*, vol. 34, no. 9, pp. 1157-1162, 2008.

[8] H.-C. Jang and H.-C. Lee, “Efficient energy management to prolong wireless sensor network lifetime,” in *Proc. of 3rd IEEE/IFIP International Conference in Central Asia on Internet, ICI 2007.*, pp. 1-4, 2007.

[9] S. Oktug, A. Khalilov, and H. Tezcan, “3D Coverage Analysis under Heterogeneous Deployment Strategies in Wireless Sensor Networks,” in *Proc. of Fourth Advanced International Conference on Telecommunications, 2008. AICT '08*, pp. 199-204, 2008.

[10] S. C. Oh, C. H. Tan, F. W. Kong, Y. S. Tan, K. H. Ng, G. W. Ng, and K. Tai, “Multiobjective optimization of sensor network deployment by a genetic algorithm,” in *Proc. of IEEE Congress on Evolutionary Computation, 2007. CEC 2007*, pp. 3917-3921, 2007.

[11] Y. Shang and H. Shi, “Coverage and energy tradeoff in density control on sensor networks,” in *Proc. of 11th International Conference on Parallel and Distributed Systems, 2005*, pp. 564-570, 2005.

[12] J. Wu and S. Yang, “Coverage issue in sensor networks with adjustable ranges,” in *Proc. of 2004 International Conference on Parallel Processing Workshops, 2004. ICPP 2004*, pp. 61-68, 2004.

[13] S. Zhang, Y. Liu, J. Pu, X. Zeng, and Z. Xiong, “An Enhanced Coverage Control Protocol for Wireless Sensor Networks,” in *Proc. of 42nd Hawaii International Conference on System Sciences, 2009. HICSS '09.*, pp. 1-7, 2009.